# PREDICTIVE TOOL FOR AIRCRAFT PLATFORMS

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**Abstract**
Article describes approach used for development of new analytical methods and procedures for interpretation of complex data gathering on board and/or from ground analysis of combat air platforms for their prediction of service status ability.

**Keywords:** diagnostic, aircraft, data mining.

## 1 Introduction

Contemporary combat air platforms are known to be an increasing complexity on the base of combination of electronic and mechanical component units are monitored by various diagnostics methods which provide very intricate complex data about this diagnostic system status saved in different databases.

In case we suppose the object of diagnostic (engine, frame, systems, etc.) is ageing part (we suppose it is high level of probability) we may have three different systems of maintenance (Scheduled Maintenance, Unscheduled Maintenance, On-condition Maintenance). The objects of diagnostic combat platforms aren't yet fully equipped by ON-LINE diagnostic systems for life status prediction and for that reason the current technical condition status depends on system life cycle and applied design philosophy for maintenance. High quantities of information recorded on-board and/or getting from on the ground analysis are produced by these systems. As the ever-higher requirements are demanded with respect to the reliability of operation such systems, also the reliability of this interaction is entailed. The only way of decreasing economical budget for service and maintenance of these systems is to strictly use modern diagnostic tools and systems.

It is not so easy to interpret relatively simply these complex data by analytical methods and procedures and it is known the only small part of these information from databases have been fully used for analysis for both commander staff decision makers and for air platform reliability improvement on the base of the predictive diagnostics. For this reason it is very important to develop a decision analysis tool for additional development of the existing databases (source information) and to get relatively simple tool for decision makers about the platform status.

The main goal of this article is describe approach used for development of the modern analytical method of the time line analysis and the graph dispersion identification for mining hidden correlations and information over experimental and the realistic date collection, both aircraft on-board and on the ground used by Czech Air Force Research Institute in Prague for combat air platform status prediction. While there are various approaches, how to improve the level of data messenger, the sophisticated analysis of data mining method with respect to possible finding of hidden information for model demo data and real data source should be taken in consideration.

## 5 Description of applied methodology

Most of the combat air platforms all over the world, the same as Czech fleet inventory, are equipped by different on-board hardware and software means for monitoring of condition and service life of the aircraft and its systems. In this paper we oriented for description of approach used for data mining from the aircraft engine database – the most import system (here and after DB TRIBO) and database parameters collected on-board (here and after DB FDR). The time lines of monitored parameters are the basic data type (rare), which can be used as input data for next development either on-board or latter on the ground. As it is well known the problem of identifying of systems life pictures in diagnostic is close contented with questions of diagnostic object modelling. This information from on-board monitoring systems consists of multidimensional diagnostic source available for additional development for maintenance optimization and for status prediction on the base correlation analyses. This idea was used in our enhancement model approach.

**Database TRIBO**

DB TRIBO (take from ground oil samples analysis) is recognized as the most useable for correlation, advanced data mining methods and next step for development of new tools according to the basic analyses. DB TRIBO consist of information (data) on the base of engine oil samples analyses of the most important metallic particles of ware (Fe, Cu, Al, Mg, Cr) for setup of concentration levels. All information within DB is hierarchic organized with aircraft and engine "id" number, oil sampling period, record of all important events (change of whole oil filling, etc.), value of concentrations, etc.

Data related to the relevant engine has been arranged according to the time line oil sampling (engine time line) – it means engine flight hours from beginning of service (flight hours to the general inspection or overhaul) – see the

**Fig**. *1*. At the figure is graphically shown progression of measured Fe concentration for actual engine. Red vertical line indicate period of engine oil change (sequence of samples). On the

**Fig**. *1* you can recognize two events (oil filling change) – it means three sequences.

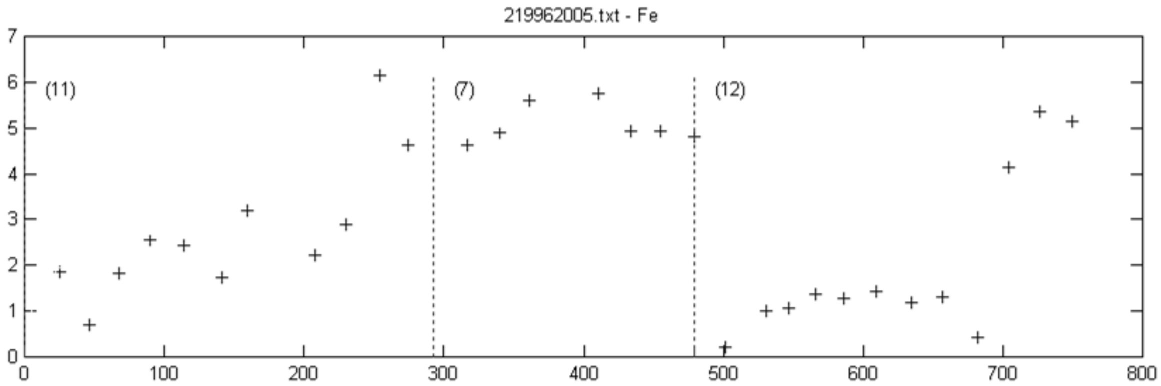


***Fig. 1*** *Time concentration period of Fe, engine type 1*

**Abnormal engine behaviour description**

Value of particles concentration level is understood here like the file of the random quantity realization with own probability distribution. On the base of distribution type it ware setup limits of critical field of phenomena with low level o probability (5% and 1%). If the value of concentration level will reach appropriate critical limits it is called here as abnormal engine symptom (indication). From historical data it is possible to setup mean value, dispersion and/or deviation and then establish warning and critical concentration – see

**Fig**. *2*.

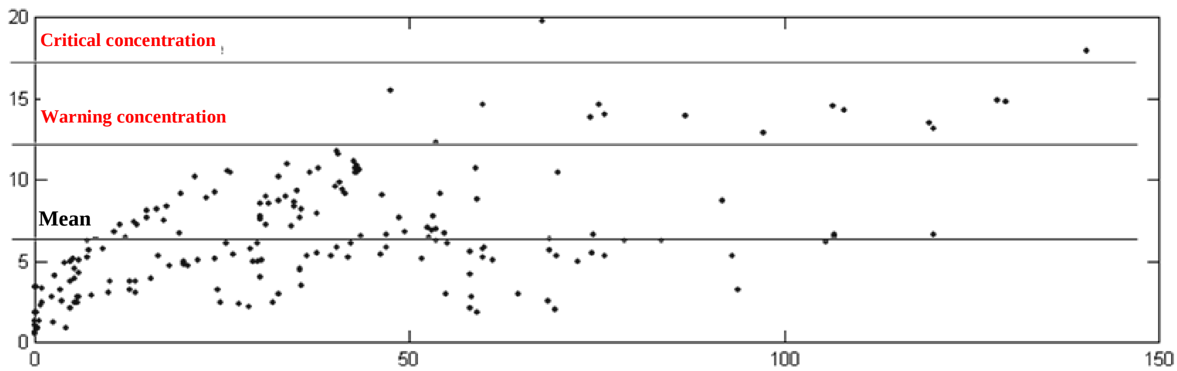


***Fig. 2*** *Definition of warning and critical concentration of abrasion metal*

On the base of time line definition we can recognize in each sequence from Picture 1 increasing time line trend and it was taken in consideration during statistical description of Tribo data as the basic step for definition of the sequence trend line model – see

*Fig. 3.*

**Procedure for modelling**

The goal of the mathematical modelling is to support detection of abnormal behaviour in aircraft engines. For development of new tools was design following approach/steps:

1. Development of Descriptive model for demo data taken from historical DB TRIBO with respect to the sequence of date samples and sequence of oil change in oil system for jet platforms and rotating wings platforms separately.
2. Development of Descriptive model by applied correlation to the DB Findings related to the demo data.

3. Testing of the Descriptive model.
4. Development of Predictive model for same condition.
5. Testing of the Predictive model.
6. Setup of limits.
7. Life verification

Description of the distribution of deviations (residuals) allows us quantitative determination of non-standard metal concentration that may indicate an engine fault. It turns out that for most couples - type of engine, used oil - the proposed prediction model generates a distribution of residuals corresponding to normal distribution. In the cases where this hypothesis will not be considered it appears to be an appropriate description the logistic distribution. The new methodology is introduced for setting the error segment. The error segment quantitatively will define the area of acceptable changes of contamination during time.

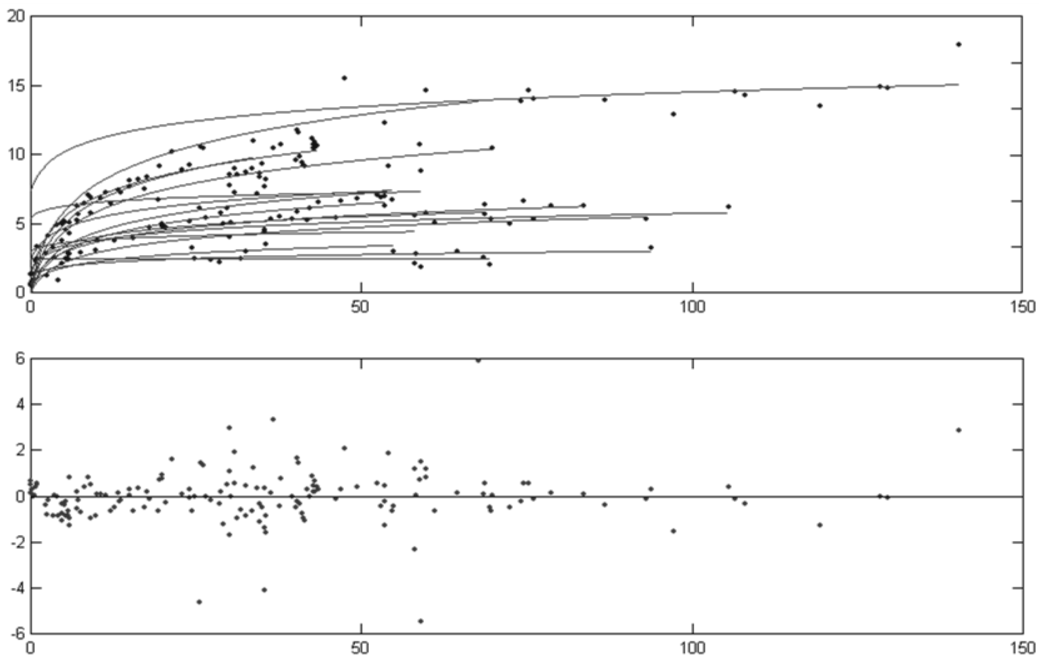


***Fig. 3*** *Trend line models for particular sequence (data, residua)*

**<u>Descriptive model</u>**

For descriptive model there were selected and tested four models with basic description as follows:

1. ***Macian*** – on the base of the weight evaluation:

$$mA(t) = mA_0 + mAr \cdot t - \int_0^t mAl(t)\, dt$$
$$mC(t) = mC_0 + \beta \cdot t - \int_0^t mAl(t) \cdot C(t)\, dt \tag{1}$$

2. ***Lotan empirical (emp)*** – on the base of the weight evaluation of metal abrasives in the oil engine filling in depends on time ***t***:

$$V(t) \cdot c(t) = V_0 \cdot c_0 + \int_0^t m \cdot dt - \int_0^t g \cdot c(t)\, dt \tag{2}$$

3. ***Logarithmic:***

$$c(t) = a \cdot \ln(t+1) + b \tag{3}$$

4. ***Linear logarithmic (LogLin):***

$$c(t) = a \cdot \ln(t+1) + bt + c \tag{4}$$

**The testing** of all **description models** have been done for four data engine types with relevant sequence (it means minimum 4 measures per sequence). The relevant sequence concept application was driven by needs of regress analyses for definition of value parameters in condition we have certain minimum measures. By using linear regression it was established parameters of trend line, sum of residual squares and appropriate dispersion ***s2*** by:

$$s2 = \frac{RSS}{n - number\ of\ parameters} = \frac{\sum_{i=1}^{n} (y_i - yreg_i)^2}{n - number\ of\ parameters} \tag{5}$$

here $\boldsymbol{y_i}$ – real measured value of concentration; $\boldsymbol{yreg_i}$ – estimated value of concentration by appropriate trend line; ***RSS*** – sum of residual squares; ***n*** – number of measurements (2 or 3) within relevant sequence of one engine type (engine family).

According to the test results over demo data for four engine types the best description was found by logarithm model without linear element (“Log model”) - equation (3).

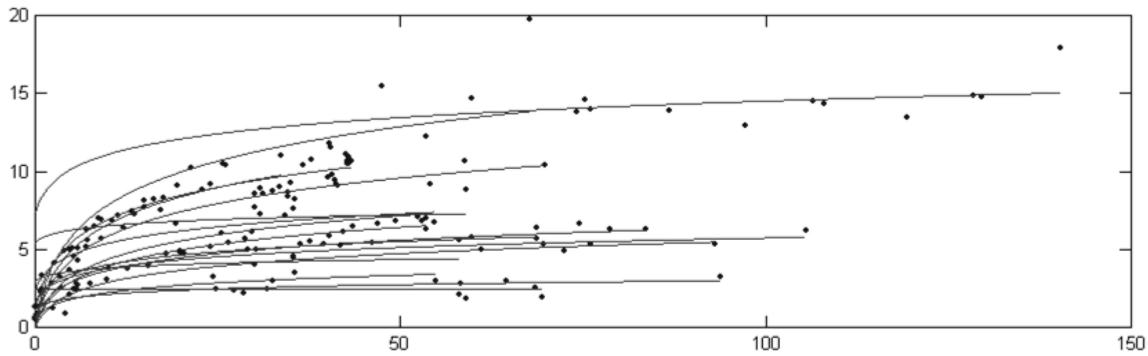


***Fig. 4*** *Concentration within one sequence modelled by Log model*

**Predictive model**

Standard engine behaviour prediction – on the base of historical date it was aim to setup parameters of predictive model. Then we were able to predict value of the expected concentration ***yreg*** at period (time) ***xp***. This concentration then has been verified by real measured value of concentration ***yp***.

The value of residua is:

$$res = yp - yreg \tag{6}$$

Standard predictive model algorithm – on the base of information from previous measurements predict value of measurement in the next period. During modelling and calculation is widely used linear regression – it was used classical linear regression by MATLAB environment/tools without limits.

Value of regression factors ***a***, ***b*** in our approximating straight-line case calculated on the base of value ($\boldsymbol{x_i}$, $\boldsymbol{y_i}$) is done by formula:

$$b = \frac{1}{n}\sum_{i=1}^{n} y_i - a\frac{1}{n}\sum_{i=1}^{n} x_i = \bar{y} - a\bar{x} \tag{7}$$

$$a = \frac{\sum_{i=1}^{n} (x_i - \bar{x}) \cdot y_i}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{8}$$

**Testing of the predictive model** has been done by similar procedure like for predictive models for four engines type data - see Table **1**.

***Table 1*** *Analysis of predictive model variance s2*

| **Fe** | **Macian model** | **Lotan model** | **LogLin model** | **Log model** |
|---|---|---|---|---|
| Engine type 1 | **3.6802** | 5.8036 | 5.3065 | 3.9355 |
| Engine type 2 | 6.6117 | 6.6128 | 6.7043 | **6.3577** |
| Engine type 3 | 1.9531 | **1.8175** | 1.8758 | 1.8272 |
| Engine type 4 | 8.7557 | 10.5197 | **8.7372** | 9.4307 |
| | | | | |
| **Cu** | | | | |
| Engine type 1 | 4.7666 | **3.6063** | 8.9382 | 4.0847 |
| Engine type 2 | 0.0479 | 0.0473 | 0.0495 | **0.0464** |
| Engine type 3 | 45.0124 | **42.9674** | 45.4486 | 43.8514 |
| Engine type 4 | 12.4100 | 12.5183 | 13.1547 | **12.3830** |
| | | | | |
| **Al** | | | | |
| Engine type 1 | 5.4283 | 5.2534 | 11.3004 | **5.1524** |
| Engine type 2 | 0.0988 | 0.1019 | 0.1008 | **0.0969** |
| Engine type 3 | 0.0768 | **0.0683** | 0.0768 | 0.0707 |
| Engine type 4 | 0.1385 | 0.1357 | 0.1454 | **0.1325** |
| | | | | |
| **Mg** | | | | |
| Engine type 1 | 0.0614 | **0.0596** | 0.0858 | 0.0651 |
| Engine type 2 | **0.0572** | 0.0647 | 0.0584 | 0.0594 |
| Engine type 3 | 0.1252 | **0.1217** | 0.1255 | 0.1232 |
| Engine type 4 | **4.6929** | 5.0935 | 5.3476 | 4.7681 |
| | | | | |
| **Cr** | | | | |
| Engine type 1 | 0.2275 | 0.0590 | 0.5745 | **0.0561** |
| Engine type 2 | 1.6789 | 2.0962 | **1.2191** | 1.8002 |
| Engine type 3 | 0.1459 | **0.1377** | 0.1491 | 0.1384 |
| Engine type 4 | **0.0340** | 0.0353 | 0.0351 | 0.0343 |

On
Fig*. **5*** you can see prediction for engine with 4 sequences (upper view predictions, lower view residua).

**Limits**

It was used analyses of residua of logarithm prediction model for definition of critical limits for abnormal engine behaviour. The goal of model construction was to achieve distribution of residua to be able describe that event – we used kvantil 95% (for warning limit) and 99% (critical limit) for event indication.

***Table 2*** *95% a 99% kvantil residua distribution of Log model*

| **95 / 99** | **Fe** | **Cu** | **Al** | **Mg** | **Cr** |
|---|---|---|---|---|---|
| Engine type 1 | 3.12 / 4.47 | 2.19 / 3.41 | 3.68 / 5.22 | 0.4 / 0.57 | 0.35 / 0.51 |
| Engine type 2 | 4.14 / 5.88 | 0.34 / 0.48 | 0.49 / 0.70 | 0.39 / 0.56 | 2.05 / 2.88 |
| Engine type 3 | 2.02 / 2.94 | 9.99 / 14.46 | 0.42 / 0.60 | 0.55 / 0.79 | 0.59 / 0.84 |
| Helicopter main gear box | 4.17 / 6.13 | 5.14 / 7.15 | 0.26 / 0.82 | 3.51 / 5.00 | 0.29 / 0.41 |

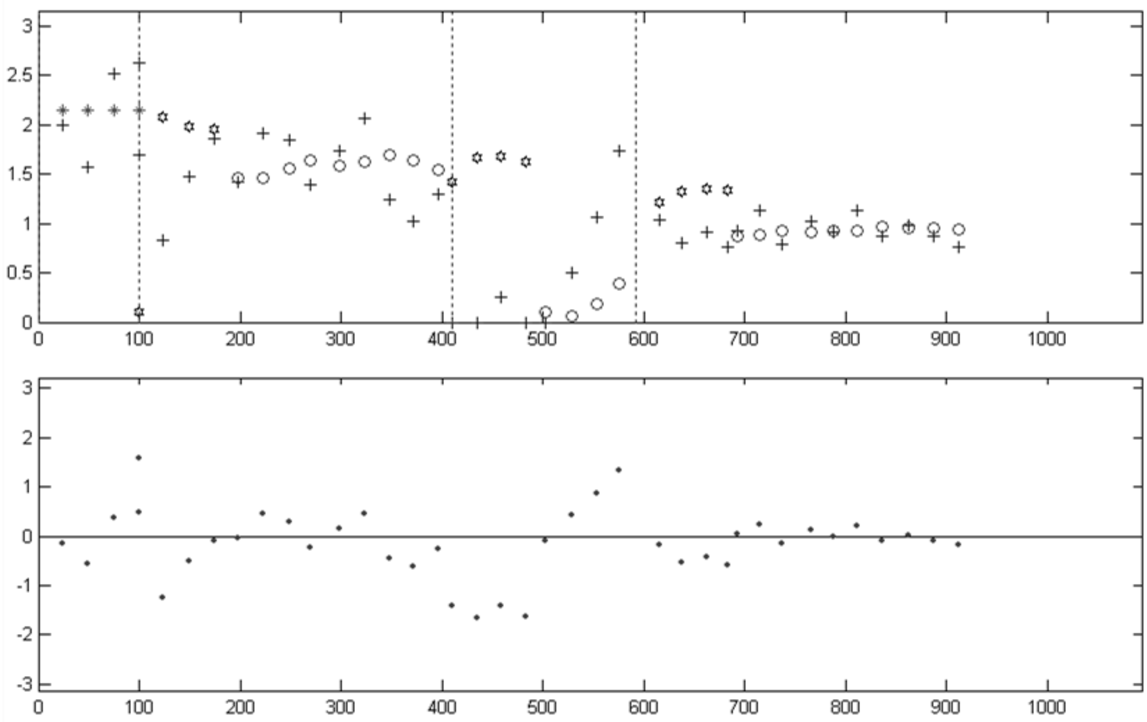

***Fig. 5*** *Sample of prediction for engine one id, type 1*

## 6 Results description

Description and Prediction models with warning and critical limits definition developed using historical engines database have been validated by historical data and events for abnormal engine behaviours – see three red circle points in

Fig. ***6***. First line means warning concentration (95% kvantil) and second one critical concentration (99% kvantil).

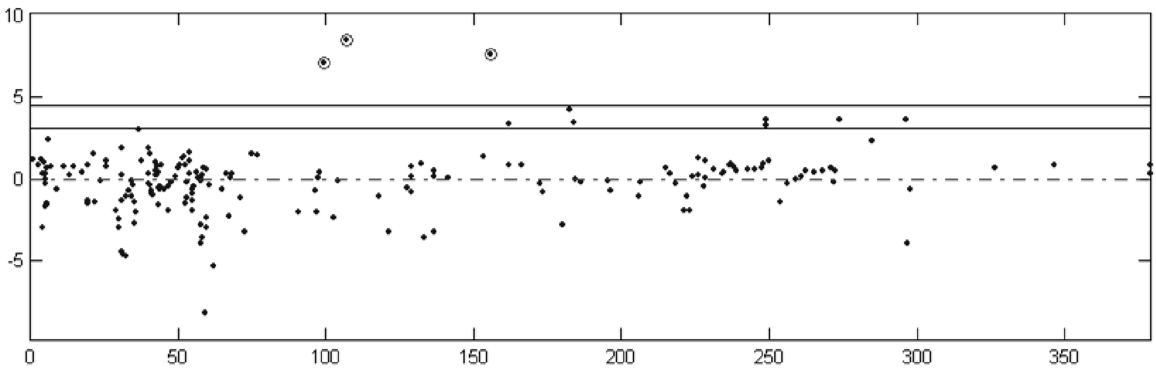

***Fig. 6*** *Sample of indication of abnormal engine behaviour*

According to the positive testing results on demo Data Base it was made suggestion for decision makers for validation and verification of procedure and models for the "life" Czech Air Force aircraft fleet.

## 7 Conclusions

The "life" verification have been arrange in two steps – pilot type of fleet aircraft (fixed wing, rotary wing and transport) without negative impact for normal maintenance procedures according to the Czech Air Force flight intensity – few warnings from predictive model have been sent to the maintenance group and findings from disassemble related units confirmed potential problems without aircraft incident investigation.

This system is used for daily regular application according to the first stage "life" verification results for whole Czech military aircraft fleet – stage two of verification. The "life" verification of Predictive model during daily regular application for Czech Air Force fleet discover two potential aircraft engine damage – it means two potential aircraft incidents.

The results of applied methodology are an enabling technology that can work across many aircraft platforms applications and, might save a loss of air platforms.

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